Problem 1

No, there is no such guarantee. There may be datapoints, which either (1) violate the margin, i.e. $0 \le \xi_i \le 1$ or (2) are on the wrong side of the hyperplane, i.e. $y_i(w^{\intercal}x_i + b) \ge 1 - \xi_i$ does not hold, in this case $\xi_i > 1$.

Problem 2

C < 0 we have from the Lagrangian of slack variables that $0 \le \alpha_i \le C$ but this obviously does not hold. If C = 0, then we have no penalty term in the optimization problem and from the Lagrangian of slack variables it follows that

$$\begin{aligned} \alpha_i &= -\mu_i \\ 0 &\leq \alpha_i = -\mu_i \\ 0 &\leq -\mu_i \end{aligned} \qquad \text{(violation of dual feasibility of Lagrangian multipliers } \mu_i \geq 0\text{)}$$

Thus C > 0.

Problem 3

We prove that $K(x,y) = (x^{\mathsf{T}}y + c)^d$ is a kernel by the construction rules.

- $K_1(x,y) = x^{\mathsf{T}}y$ is a kernel by Rule 5, where B = I.
- $K_2(x,y)=c$ is a kernel by Rule 4, where $\phi(z)=\sqrt{c}, \phi:\mathbb{R}^n\to\mathbb{R}^m, m=1$ and $K_3(x,y)=x^\intercal y$
- $K_3(x,y) = K_1(x,y) + K_2(x,y)$ is a kernel by Rule 1
- $K_4(x,y) = K_3(x,y)^d$ is a kernel by recursive application of Rule 3

Thus $K(x,y) = (x^{\mathsf{T}}y + c)^d$ is a valid kernel.

Problem 4

No, we can not apply it directly to our data because the feature map is infinite dimensional. For this we would need to define a representation of the inner product of two infinite vectors $\phi_{\infty}(x)$, $\phi_{\infty}(y)$ as a function $K(x,y) = \phi_{\infty}(x)^{\mathsf{T}}\phi_{\infty}(y)$.

Problem 5

Problem 6

Problem 7

$$||x - x^{(s_i)}||_2 = \sqrt{\sum_{j=1}^{M} (x_j - x_j^{(s_i)})^2}$$

$$= \sum_{j=1}^{M} (x_j - x_j^{(s_i)})^2 \qquad \text{(squared distance does not change k nearest neighbors of } x)$$

$$= \sum_{j=1}^{M} (\phi(x_j) - \phi(x_j^{(s_i)}))^2 \qquad \text{(by feature map } \phi(x))$$

$$= (\phi(x) - \phi(x^{(s_i)}))^{\mathsf{T}} (\phi(x) - \phi(x^{(s_i)}))$$

$$= \phi(x)^{\mathsf{T}} \phi(x) - 2\phi(x)^{\mathsf{T}} \phi(x^{(s_i)}) + \phi(x^{(s_i)})^{\mathsf{T}} \phi(x^{(s_i)})$$

$$= K(x, x) + K(x^{(s_i)}, x^{(s_i)}) - 2K(x, x^{(s_i)})$$